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Detecting Dental Epidemics

Dental diseases are typically regarded as if they were non-communicable. For this reason, training in methods appropriate to the analysis of classical epidemics is not common during dental education. Recent emphasis on the control of cross-contamination potentials would seem to enhance the importance of epidemiological monitoring of disease outbreaks. Monitoring allows for the identification of unusual clustering and perhaps eventually to the determination of causative agents.

Disease related events (henceforth simply called events) may cluster in either space or time. The critical statistical issue is whether clustering of particular magnitudes is unusual or could have resulted from chance fluctuations. Clustering in space (e.g. differences in event rates between geographic areas or practitioners) can be detected using a variety of well documented statistical techniques (1,2). In general, statistical methods are used to determine whether or not there are significant differences among proportions or counts.

These methods, as well as others including the cluster index (3) and cumulative sum (CUSUM) (4), can also be used to evaluate the consistency of event rates between time intervals. If ungrouped (by time period) data are available, these techniques are not optimal because they discard information. An epidemic may not be detected simply because its occurrence overlaps the end of one arbitrary interval and the beginning of the next.

The purpose of this paper is to describe efficient methods for the statistical analysis of continuous time distributions of dental events. A single data example is chosen but the methods could apply in a variety of situations. The following data could conceivably represent post-surgical complications following removal of third molars, periapical infections following a first phase of endodontic treatment, and so forth.

The Data Set

Figure 1 describes the incidence of diagnosed pericoronitis (PCOR) among personnel of a U.S. aircraft carrier during the final 140 days of a six-month Mediterranean cruise during 1987. Data collection began immediately upon arrival of the second author to the carrier's dental department. The great majority of personnel were on board for the entire cruise but the ships compliment did vary between approximately 4,600 and 4,700. There were 12 reported cases of PCOR, but these fell into two 5-case clusters of eight and seven days duration.

If events distribute themselves within a time interval according to a random process, they should be uniformly distributed across the observational period. Although the two clusters beginning on days 41 and 130 seem unusual and non-random, specification of a probability statement is required for

inferential purposes.

Several statistical techniques will be applied to this data. In actual practice, the use of multiple tests and the selection of tests after the data have been examined, reduces statistical validity (which may not be a serious problem when intentions are exploratory). The null hypothesis will always be that the PCOR events were distributed uniformly during the 140 days of observation while the alternate hypothesis will be that the sample could not have been selected from a uniform distribution of events (at $p<.05$).

Kolmogorov-Smirnov

The most well-know test that can be applied to this data is the Kolmogorov-Smirnov goodness-of-fit test (5,6). The basic idea behind this test is to identify the maximum, absolute value, deviation between the sample cumulative distribution, $F_s(x)$, and the theoretical cumulative distribution, $F_t(x)$. The test statistic D is defined as:

$$D=\max|F_s(x)-F_t(x)|.$$

This value can be determined graphically by inspecting the cumulative distributions or computed algebraically. If computed, it is important to recognize that the largest vertical difference between $F_s(x)$ and $F_t(x)$ may not occur at an observed value of x (6). An algebraically valid value of D is:

$$D=\max\{\max[|F_s(x_i)-F_t(x_i)|,|F_s(x_{i-1})-F_t(x_i)|]\}.$$

If this value exceeds the tabulated value, the hypothesis that the sample came from the theoretical distribution is rejected.

In this case, the theoretical distribution is the uniform so each day should produce 1/140th of the total number of cases. Sample and theoretical cumulative distributions, and differences between them as each case is identified are shown shown in Table 1 and Figure 1. D=0.3452 and p=.09 (by linear interpolation of tabled values) so the hypothesis of a uniform distribution is not rejected.

Kuiper

Kuiper's goodness-of-fit test (7) has been shown to be more sensitive to departures from randomness except when they involve marked crowding of points on only a single end of the time line (8). Since this is not true of our data, this test might be a more powerful alternative. The data in Table 1 may also be used to calculate Kuiper's test statistic K which is defined as:

$$K=\sqrt{n}(D^{+}+D^{-}),$$

where n = the number of cases, D^{+} is the largest positive value of $F_s(x)-F_t(x)$ and D^{-} is the absolute value of the largest

negative value, again with proper consideration for the location of the largest vertical difference. For the PCOR incidence data, K=3.4641(0.1571+0.3452)=1.7400 and p=.03 (by linear interpolation of tabled values) and the null hypothesis is rejected.

Watson

Instead of the two maximum deviations used in Kuiper's test, Watson's goodness-of-fit test (7) uses a mean square deviation. It appears that this test is especially powerful for small sample sizes and is suitable for both unimodal and multimodal data. The two separated clusters in the PCOR data suggests possible application in this case. Watson's U^2 statistic is defined as:

$$U^2=SUM(F(x)^2)-SUM(cF(x)/n)+n(1/3-(MEAN(F(x))-0.5)^2),$$

where c=2i-1 and i is the event number from 1 to n. In this case, $U^2=5.3878-9.1167+12(1/3-(7.1/12-0.5)^2)=0.1703$ and p=.07 (by linear interpolation of tabled values). Although not statistically significant (at p<.05), the results of the Watson test might might lead the researcher to consider the alternate hypothesis worthy of continued investigation.

Scan

If there is any information on the conjectured duration of an epidemic, the scan statistic (10) may be a more powerful alternative to the methods previously described. "The scan statistic is the maximum number of observed cases in an interval of preselected length, as the interval is allowed to scan, or slide along, the time frame of interest." Suppose that the investigator, because of anecdotal reports (this is fictitious), believed that PCOR incidence would be greatest for seven day periods following liberties in foreign ports. The scan interval is set to seven days and the value of the scan statistic would be five (cases). The significance level for this statistic, P(n,N,r), for a particular n (maximum cases in the scan interval), N (total number of cases identified), and r (ratio of scan interval to total period of observation) can be determined from tabled values (10) or approximated by P (11),

$$P(n,N,r)=P=(n/r-N+1)Pr(Y=n)+2Pr(Y\geq n+1),$$

where Y has a binomial distribution with parameters N and p=r;

$$Pr(Y=n)=N!r^n(1-r)^{N-n}/((N-n)!n!).$$

A short algorithm (in IBM PC BASIC) to compute P for small N is found in the appendix.

For our data n=5, N=12, and r=7/140=1/20 and p=.015. Thus the null hypothesis would be rejected. This technique, however is dependent upon selection of an appropriate interval which requires prior knowledge about durations of hypothesized point epidemics. If the interval had been selected as 10 days then

p=.052, and if 14 days then p=.149. Thus, statistical significance in this case would have resulted from a fortuitous interval selection. In general, the sort of information necessary for an informed selection of interval length would not usually be available in exploratory studies and selection after the data are seen would lead to invalid alpha error estimates.

It should also be noted that the same a priori information that would allow a good selection of interval length might also be used to categorized time periods as an independent variable. For this data, counts while underway for at least seven days versus counts within seven days after port liberty could be used. As such, other more traditional techniques may be applied. In this case, a statistical test for differences between two Poisson counts (2), adjusted for population-time, would be a good alternative.

Application in the Dental Setting

Detection of unusual disease event clusters has inherent clinical value due to current emphasis on quality control and risk management. The procedures that have been described are relatively simple methods that will allow an investigator to apply a probabilistic criterion to clustering during a time period.

Kolmogorov-Smirnov, Kuiper, Watson, and Scan statistics differ in power and necessary a priori information that would lead to their selection. In the absence of prior knowledge about the particular type of epidemic being investigated, Kuiper's test appears to be the best choice.

These methods are appropriate to a single retrospective analysis of a data set. Should an epidemic potential be identified for particular infections or complications, it is appropriate that implementation of continuous monitoring be considered. Such surveillance methods may, for example, involve the comparison of current rates to historical risk or CUSUM continuous monitoring (11). These ongoing methods will enhance the possibility of identifying as yet unknown causative agents.

References

1. Fleiss JL. Statistical Methods for rates and proportions, 2nd ed. New York: John Wiley and Sons, 1981.

2. Woolson RF. Statistical methods for the analysis of biomedical data. New York: John Wiley and Sons, 1987.

3. Tango T. The detection of disease clustering in time. Biometrics 1984; 40:15-26.

4. Levin B, Kline J. The CUSUM test of homogeneity with an application in spontaneous abortion epidemiology. Stat Med 1985; 4: 469-88.

5. Massey Jr FJ. The Kolmogorov-Smirnov test for goodness of fit. J Am Stat Assoc 1951; 46: 68-71.

6. Daniel WW. Biostatistics: A foundation for analysis in the health sciences, 3rd ed. New York: John Wiley and Sons, 1983; 405-11.

7. Batschelet E. Circular statistics in biology. London: Academic Press, 1981; 76-81.

8. Pearson EA. Comparison of tests for randomness of points on a line. Biometrika 1963; 50: 315-25.

9. Wallenstein S. A test for detection of clustering over time. Am J Epidemiol 1980; 111: 367-72.

10. Wallenstein S, Neff N. An approximation for the distribution of the scan statistic. Stat Med 1987; 6: 197-207.

11. Weatherall JAC, Haskey JC. Surveillance of Malformations. Br Med Bull 1976; 32: 39-44.

DATA TABLE FOR COMPUTING KOLMOGOROV-SMIRNOV D, KUIPER K, AND WATSON U^2 STATISTICS

Days of Observation = 140
Number of Cases Identified = n = 12

Case (i)	Day	$F_s(x)$	$F_t(x)$	$F_s(x)-F_t(x)$	$F_s(x_{i-1})-F_t(x)$	c	$F_t(x)^2$	$cF_t(x)/n$
1	28	1/12	28/140	-0.1167	-0.2000	1	0.0400	0.0167
2	41	2/12	41/140	-0.1262	-0.2095	3	0.0858	0.0732
3	44	3/12	44/140	-0.0643	-0.1476	5	0.0988	0.1310
4	45	4/12	45/140	0.0119	-0.0714	7	0.1033	0.1875
5	46	5/12	46/140	0.0881	0.0048	9	0.1079	0.2464
6	48	6/12	48/140	0.1571(+)	0.0738	11	0.1176	0.3143
7	74	7/12	74/140	0.0548	-0.0286	13	0.2794	0.5726
8	130	8/12	130/140	-0.2619	-0.3452(-)	15	0.8622	1.1607
9	131	9/12	131/140	-0.1857	-0.2690	17	0.8756	1.3256
10	135	10/12	135/140	-0.1310	-0.2143	19	0.9298	1.5268
11	136	11/12	136/140	-0.0548	-0.1381	21	0.9437	1.7000
12	136	12/12	136/140	0.0286	-0.0548	23	0.9437	1.8619
	SUM		7.1000				5.3878	9.1167

Unless otherwise noted, the subscript assigned to x in "(x)" is i. (+) is the largest positive difference and (-) the largest negative difference between the sample and theoretical distributions.

APPENDIX

Program for computing P for the scan statistic when N is small

```
10  'ENTER APPROPRIATE VALUES IN NEXT THREE LINES'
20 N=12     'N=TOTAL NUMBER OF CASES FOUND
30 R=1/20   'R=RATIO OF INTERVAL SIZE TO TOTAL PERIOD
40 S=5      'S=n=MAXIMUM NUMBER OF CASES FOUND IN MOVING INTERVAL
50 P=0
60 FOR J=0 TO S
70 NUM=1:DEN=1
80 FOR I=(N-J+1) TO N:NUM=NUM*I:NEXT I
90 NUM=NUM*(R)^J*(1-R)^(N-J)
100 FOR I=1 TO J:DEN=DEN*I:NEXT I
110 PR=NUM/DEN:P=P+PR
120 PRINT USING "#.######  ";PR,1-P
130 NEXT J
140 PRINT
150 PRINT "PROBABILITY(S,N,R) = "
160 PRINT USING "#.######";(S/R-N+1)*PR+2*(1-P)
170 END
```

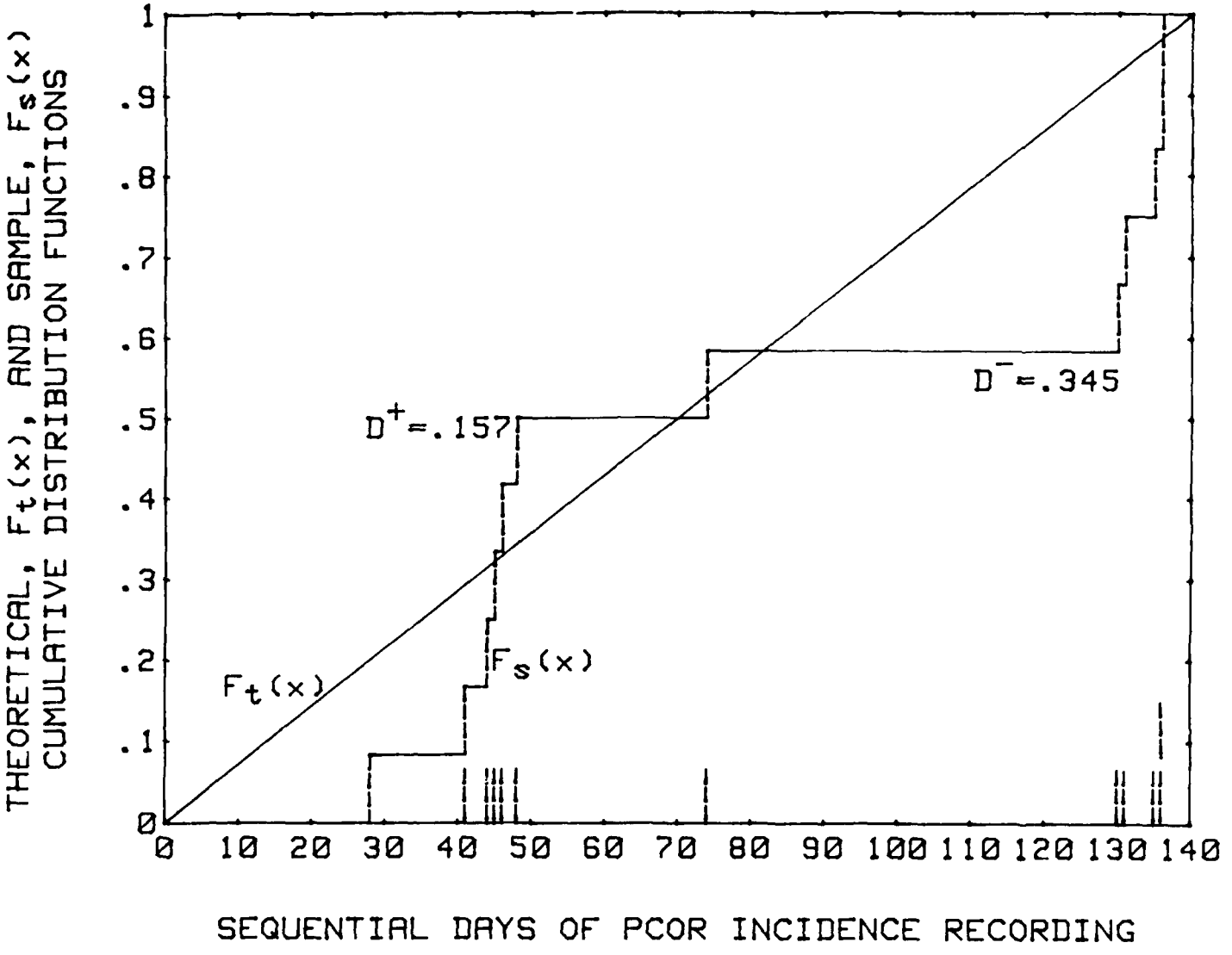

Figure 1. Theoretical, $F_t(x)$, and Sample, $F_s(x)$, cumulative distribution functions for the PCOR data. The theoretical distribution is the uniform and D^+ and D^- are maximum positive and negative differences between the empirical data and this distribution. The lines on the x-axis indicate the incidence of events which are added to the cumulative sample distribution. Both the Kolmogorov-Smirnov and Kuiper test statistics can be estimated graphically or algebraically.

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Because dental disease has not been generally considered communicable, epidemic detection was unnecessary in most dental settings. Contemporary emphasis on infection control, however, has now made the detection of infection and complication "outbreaks" a justifiable quality control activity. When there are identifiable independent variables (e.g., practitioner, clinic, or procedural change) investigators are directed to well documented methods that allow comparisons of proportions or

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counts amor, groups. Alternately, an investigator may simply want to examine disease related events over time for evidence of rate changes. The present paper describes four statistical techniques for detecting this type of clustering and applies them to the analysis of apparent pericoronitis point epidemics on a US aircraft carrier.